Multimodal Sequence Learning with a Cortically-Inspired Model

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Abstract

We present in this paper a cortically-inspired model that learns to exploit regularities of sequences of perceptions and actions, with regard to motivations. Sequences are learned from continuous multimodal information streams, on the basis of a competition mechanism. This approach enables generalisations from perceptive regularities and also ensures the capability to apply results of previous learning to help further learning of new tasks.

1. Introduction

Our approach aims to show that a cortically-inspired model enables a system to build internal representations of the regularities of its environment in order to perform an efficient selection of action. As we describe in the paper, these representations, more expressive than the Q-values, are based on competition and multimodality integration. They allow the system to learn sequences of actions toward its internal goals.
Though inspired with neurobiological data, the model that we propose below is mainly a functional view of the cortex and thus a very rough description of it. We are more precisely interested in the way the cortex can combine external perceptions with learned spatio-temporal regularities and internal drives.

2. Our cortical model

2.1 Main structures

Maxicolumns The cortex is the "upper" part of the brain of superior mammalians. It appears as a 2D sheet of replicated similar neural structures called cortical columns (Burnod, 1989). Sets of contiguous columns are gathered to form packs called maxicolumns. Maxicolumns contain columns that receive the same information stream. If no learning occurs, all the columns of a maxicolumn are synchronously firing. Learning will then consist in splitting the maxicolumn in sets of columns, each set firing on specific patterns of the information stream received by the maxicolumn (feature coding columns). Each set of columns can split again if a more accurate discrimination is needed in the future. Information streams coming from various parts of the cortex, and information patterns being generally temporal patterns, this specialisation mechanism will also have to detect sequences, i.e. succession of maxicolumns' activations. This kind of specialisation explains why columns are generally described as functional units or as representing goals, since their activation is synonymous for internal or external event detection. The perceptive events that make maxicolumns fire can be viewed as the basic events that the cortex can manipulate and combine.

Cortical maps The cortical sheet can be divided in functional maps, according to the nature of the information the maxicolumns of a particular area receive. For example, the maxicolumns of the primary visual map all get information from different parts of the retina. There is a mono-modal map for each sensory-motor modality (auditory map, motor map, somesthesic map...).
Most cortical maps do not only work on mono-modal streams, but combine several streams. We will here consider the number of associated modal streams to be only two. These maps are called associative maps, in which maxicolumns receive bi-modal patterns. Higher levels of multi-modal associations are provided by associative maps that combine information streams from two "lower" associative maps. Details about connectivity of associative maps can be found in (Ballard, 1986).
The power of mammalian cortex seems to be grounded on this architecture, using competitive learning and competitive activation to exploit spatio-temporal invariants at different levels of abstraction. We now present our view for the local functioning of a maxicolumn, considered as the basic constitutive element of the cortex.

2.2 Management of information streams inside a maxicolumn

Information streams A maxicolumn mainly combines three kinds of streams, as shown on figure 1. The **feed-forward** streams are the ones described above, directly corresponding to external and internal perceptions or to a combination of perceptions provided by associative maps. An associative map receives two feed-forward streams.

Second, the **lateral** streams come from other maxicolumns in the same map. They are control streams, involved in inhibition mechanism and sequence construction (sequences are learned between maxicolumns in the same map as described in section 2.3).
Third, the **feed-back** streams come from upper maps that associate to other maps the map the maxicolumn belongs to.

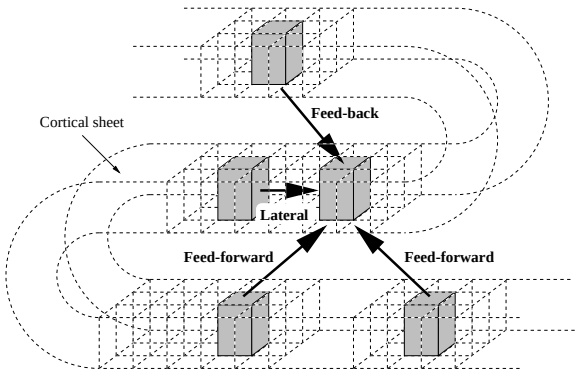

Figure 1 A maxicolumn combines three main kinds of information streams.

Activations In addition to the classical excitation state of a column, representing the realisation of the goal that the column represents, two other activation states ("call" and "satisfaction") are brought in our model. They allow to consider that an event can be called by a desired goal for its satisfaction.
The **excitation** variable is firing when the maxicolumn "recognizes" in the feed-forward stream the pattern it is tuned on. For associative maxicolumns, this pattern will be in our model restricted to the product of the two feed-forward excitations. Multiplication is viewed as a logical "and" (see (Alexandre and Guyot, 1995)).
A maxicolumn having "call" activity asks for the occurrence of the perceptive event that usually fires the maxicolumn (cf. (Burnod, 1989), (Blanchet, 1994)). Calls are initiated by physiological drive on particular maxicolumns, and spread in the cortex through feed-forward and feed-back paths. Note that a maxicolumn never receive a call from an excited maxicolumn, because the excitation of the latter maxicolumn has occured and must not be asked anymore.
This propagation mode is wide and the number of called maxicolumns has to be reduced from the set of excited maxicolumns and the associations the cortex has learned in the past. An inhibitory mechanism, discussed below, enables to sustain only **relevant calls**.
We say that a maxicolumn is **satisfied** if it is simultaneously called with relevance and excited : the event the cortex is asking for occurs.

2.3 Learning sequences

We mention here two ways of learning sequences. First, the connection between an event and another one that is assumed to be its cause can be viewed as a short sequence learning. Those associations occur if the satisfaction of a maxicolumn often occurs when one of the maxicolumns it is connected with through feed-back paths is satisfied. For example, consider two maps respectively coding events a, b, c and events α, β, γ and an associative map coding events like a/β and a/γ. If an event a is called, and if it is more often satisfied at the same time as the associative maxicolumn a/β than a/γ, β will be considered as the cause of the excitation of a. The events a and β from distinct maps will be associated by a reinforcement on the weight of the feed-forward path from a to the associative column a/β.
The second way of learning sequences consists in extracting causality chains of number of events **in the same map**. Here, the lateral streams will have the following functionality : if a maxicolumn a is often satisfied after the excitation of a maxicolumn b in the same map, b is assumed to be one of the possible events required for the occurrence of a. Then, calling b is useful when a is called. This utility of b will be realized by reinforcing the lateral path from a to b so that the call of a can generate a call of b. b **is said to be a sub-goal of the goal** a. Actually, the mechanism we have implemented is a little more complex : when the maxicolumn b is detected as a sub-goal of a, it splits into two maxicolumns, one having the same behaviour as the maxicolumn b before splitting, the other being tuned to receive calls from a. That mechanism ensures that a maxicolumn can be a subgoal of two distinct maxicolumns, without a merging of sequences (see figure 2)

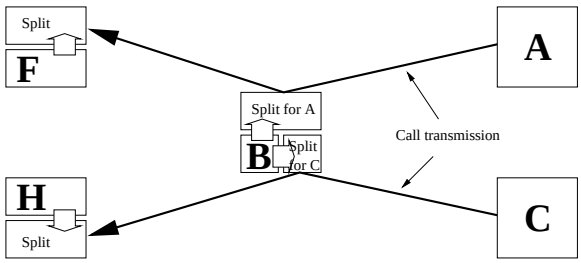

Figure 2 Because of the splitting mechanism, sequences $F \leftarrow B \leftarrow A$ and $H \leftarrow B \leftarrow C$ do not merge in B.

2.4 Computing relevant calls

We have pointed out the need to constraint the spread of calls to relevant calls. The constraint of calls is obtained by a competition between **all called maxicolumns of the same map and them only**. Each column computes a competition value, and the maxicolumns whose competition value is lower than the maximum competi-

tion value of the maxicolumns in the map are inhibited, through lateral paths (the maxicolumns of a map are totally connected through lateral paths). **A call of an inhibited** (i.e. a non relevant-called) **maxicolumn only circulates through lateral path sequences**, but not through feed-back and feed-forward paths. This inhibition mechanism acts as a filter of "vertical" calls. We give hereafter the different criteria used to compute the competition value of a maxicolumn a, ordered from the most relevant to the less significant.

1. The strength of call in a : this criterion enables the cortex to solve the most critical problems first.
2. The excitation of B, if the sequence $\cdots \leftarrow B \leftarrow A \leftarrow \cdots$ has been learned. Thus, the maxicolumns that are called from learned sequential paths and whose sub-goal is obtained are favoured. They are supposed to be the "next step" to the satisfaction of the drive.
3. The call that a receives through feed-back paths : this call is the result of the competition of an "upper" map.
4. Maximal excited pre-conditions of a : this value is computed if a is a successor of a goal G which have relevant call, (i.e. $\cdots \leftarrow A \leftarrow \cdots \leftarrow G \leftarrow \cdots$). The value computed is the max of the excitation of the maxicolumns a receives feed-forward from. If a associates lower events α and β, we consider the excitation of one of them as a precondition to excitation of the other. Perceptive maxicolumns are considered as conditions producing a call on actions. This is thus not possible with the excitation of motor maxicolumns.
5. The relevant call that a receives, coming from feed-forward paths corresponding to the first way of learning sequences described above : a maxicolumn from a "lower" map needs the occurrence of the other associated event to fire.

2.5 Action release

After competitive filtering, only relevant calls survive in the cortex. The call propagation mechanism aims to apply relevant calls on maxicolumns of primary motor maps, each of them coding a possible action. If an action is relevant-called, and if the constraints of the environment enables this action to succeed, the corresponding motor maxicolumn will fire so that it becomes satisfied.

3. Implementation

3.1 The maxicolumn

As we said before, columns, and thus maxicolumns, can be viewed as autonomous automata, each combining in an unsupervised way the streams it receives. Each automaton has the same transition function f, that computes the value of the state variables X at the next step from current X and current inputs, storing the result in registers X_tmp. First, each automaton computes $X\_tmp = f(X, IN)$ and when they all have done this job, each makes a copy from X_tmp to X. This classical method ensures that a sequential evaluation of the automata will not depend on the order in which the automata are computed (see figure 3).
Then, we say that a maxicolumn a is connected to a maxicolumn b when the outputs of b are some of the inputs of a. This mechanism is relative to the biological fact that dendrites of a "read" the state of b through synaptic connection to the axon of b.

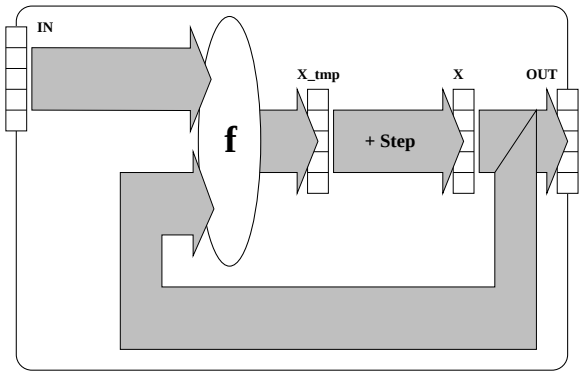

Figure 3 Order-independent evaluation mechanism.

3.2 Sequence management

We give in this section some general programming principles that carry out the learning of temporal invariants among the maxicolumns of a map, as discussed in section 2.3.

Learning rules General temporal-learning mechanisms can be found in (Sutton and Barto, 1981). The temporal learning rules we used are based on the hypothesis that only regularities concerning called maxicolumns have to be learned. This learning paradigm allows the cortex to select from all the regularities of its perceptive environment those which satisfied one of the sub-goals of a drive. This restriction prevents from learning contingencies of all patterns of perception in every cases, contingencies that would be all of the same weak strength.
As Sutton and Barto did in (Sutton and Barto, 1981), we derive our rule from the Rescorla-Wagner rule (see (Allan, 1993)) to evaluate contingency of events. This rule is here considered as a competitive method to select among several events e_i **the ones** that predict the occurrence of a goal-event G. Let E be the set of all possible predictor events and E_t^+ the set of the events in E that occur at time t. The Rescorla-Wagner rule computes the strengths V_i of associations between each e_i and G as follows :

$$dV_i = \alpha_i(t)(\lambda_G - \sum_{e_j \in E_t^+} V_j) \quad \text{if } e_i \in E_t^+$$

$$dV_i = 0 \quad \text{otherwise}$$

The α_i coefficients are the efficiencies of the e_i, and may be different whether G occurs at time t or not. λ_G is a positive constant if G occurs at time t and is null otherwise.
In order to build sequences, we want to find which maxicolumn M_i has an excitation e_i that predicts the **future** satisfaction of a maxicolumn G. The learning mechanism will be effective **only if G has a relevant call**. A maxicolumn M_i is said to be at the state `active` if its excitation occured t time-unit ago, t being lower than a maximum period τ. If $t = \tau$, the maxicolumn is at the state `end`. Otherwise, the maxicolumn is at the state `inactive`. During the active state of M_i, the efficiency α_i exponentially decreases, starting from a constant α. G continuously computes the sum $\Sigma_G(t)$ of all active M_i at time t. The table 1 shows learning rules that we propose.

<table>
<tr><th></th><th colspan="2">States of M_i</th><th></th></tr>
<tr><th></th><th>active</th><th>end</th><th>inactive</th></tr>
<tr><td>Satisfaction of G occurs.</td><td colspan="2">$dV_i = \alpha_i(t)(\lambda_G - \Sigma_G(t))$
Now G considers that M_i is inactive, until M_i becomes excited again.</td><td rowspan="2">$\emptyset$</td></tr>
<tr><td>Relevant call in G.</td><td>$\emptyset$</td><td>$dV_i = -\beta\Sigma_G(t)$
The fact that M_i is not considered as inactive implies that M_i wasn't active the last time G was satisfied.</td></tr>
<tr><td>otherwise</td><td colspan="3">$\emptyset$</td></tr>
</table>

Table 1 Adapted Rescorla-Wagner learning rules. $\emptyset$ means "no learning".

These rules tend to reinforce weights that correspond to the most frequent and closest predictor in time (because of the decrease of $\alpha_i(t)$). When the weights reach their asymptotic values, the strongest weights, if stronger enough, yield the maxicolumns considered to be sub-goals of G.

Splitting As we have one automaton per maxicolumn, we create a new automaton when splitting occurs. This new automaton, representing the fact that the initial maxicolumn is a sub-goal of the goal-maxicolumn, must have the same connection as the initial maxicolumn, with a specialisation of the lateral path from the goal that enables the sub-goal to receive calls from the goal. Compared with the initial maxicolumn, this new sub-goal is much stronger in Rescorla-Wagner competition. As a consequence, the system rather tends to extend existing sequences than to begin a new one from the same maxicolumn.

Sequence improvement With same mechanisms as sequence building, a sub-goal can check the ability of its satisfaction to predict satisfaction of the goal. We call this capacity the **efficiency** of the sub-goal (see (Blanchet, 1994)). A mechanism of cleaning sub-goals that finally appears to be non efficient enough is implemented.

4. Discussion

The main objective of this paper was to show that our cortical model enables a system endowed with perceptions and actions to learn regularities of the external world and strategies to select relevant actions. The main feature of our model we wished to present here is sequence learning, as a consequence of competitive mechanisms and information streams merging.
This cortical model has been assessed on a behavioral learning task. The task consists in exploiting the image that a robot receive from a video camera to choose among possible actions like "eating", "drinking", "going ahead", "turning left" and "turning right", according to the level of internal vital needs. The system correctly associates the features of that environment, and endly knows that food is red and must be eaten, that a good way to reach a food area is to turn until it is centered on the image, an then to go straightforward, etc...
This experience reveals that our model provides an interesting capability of multimodal sequence extraction and use, and build integrated reactive behavior. Nevertheless, it clearly shows the lack of such an associative approach to provide planning capabilities. From that matter of fact, we now work on a prefrontal model that might successfully complete our current model.

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